Prognostic Enhancements to Gas Turbine Diagnostic Systems [1]

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Abstract— The development of machinery health monitoring technologies has taken center stage within the DoD community in recent years. Existing health monitoring systems, such as the Integrated Condition Assessment System (ICAS) for NAVSEA, enable the diagnosis of mission critical problems using fault detection and diagnostic technologies. These technologies, however, have not specifically focused on the automated prediction of future condition (prognostics) of a machine based on the current diagnostic state of the machinery and its available operating and failure history data. Current efforts are focused on developing a generic architecture for the development of prognostic systems that will enable "plug and play" capabilities within existing systems. The designs utilize Open System Architecture (OSA) guidelines, such as OSA-CBM (Condition Based Maintenance), to provide these capabilities and enhance reusability of the software modules. One such implementation, which determines the optimal water wash interval to mitigate gas turbine compressor performance degradation due to salt deposit ingestion, is the focus of this paper. The module utilizes advanced probabilistic modeling and analysis technologies to forecast the future performance characteristics of the compressor and yield the optimal Time To Wash (TTW) from a cost/benefit standpoint. This paper describes the developed approach and architecture for developing prognostics using the gas turbine module.

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1. INTRODUCTION

Various prognostics and health monitoring technologies have been developed that aid in the detection and classification of developing system faults. However, these technologies have traditionally focused on fault detection and isolation within an individual subsystem. Health management system developers are just beginning to address the concepts of prognostics and the integration of anomaly, diagnostic and prognostic technologies across subsystems and systems. Hence, the ability to detect and isolate impending faults or to predict the future condition of a component or subsystem based on its current diagnostic state and available operating data is currently a high priority research topic.

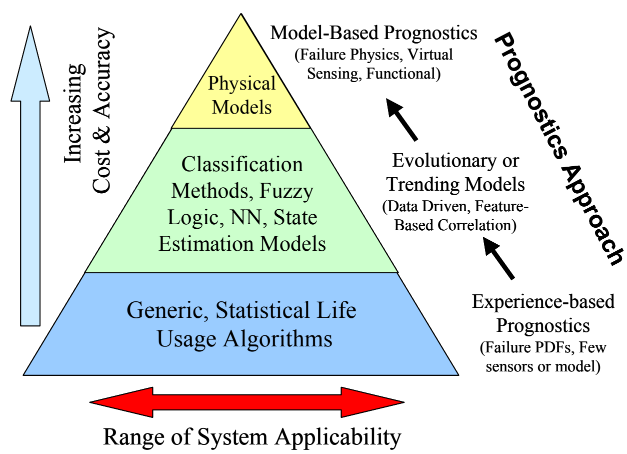

Figure 1 – Hierarchy of Prognostic Approaches

In general, health management technologies will observe features associated with anomalous system behavior and relate these features to useful information about the system's condition. In the case of prognostics, this information relates to the condition at some future time. Inherently probabilistic or uncertain in nature, prognostics can be applied to

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system/component failure modes governed by material condition or by functional loss. Like diagnostic algorithms, prognostic algorithms can be generic in design but specific in terms of application. Various approaches to prognostics have been developed that range in fidelity from simple historical failure rate models to high-fidelity physics-based models. Figure 1 illustrates a hierarchy of prognostic approaches in relation to their applicability and relative costs.

This paper will discuss some architectures and specific prognostic implementations for gas turbine engines. The ability to predict the time to conditional or mechanical failure (on a real-time basis) is of enormous benefit and health management systems that can effectively implement the capabilities presented herein offer a great opportunity in terms of reducing the overall Life Cycle Costs (LCC) of operating systems as well as decreasing the operations/maintenance logistics footprint.

2. US NAVY ICAS

The Navy's Integrated Condition Assessment System (ICAS) [1] is a tool to enable maintenance troubleshooting and planning for shipboard machinery systems. It provides data acquisition, data display, equipment analysis, diagnostic recommendations, and decision support information to operators and maintenance personnel. Additionally, ICAS links to other maintenance-related software programs to provide a fully integrated maintenance system. ICAS assesses equipment and system condition for maintenance of machinery and equipment. Through the use of permanently installed sensors, the ICAS system monitors vital machinery parameters on a continuous basis. ICAS can diagnose the operational condition of a particular piece of machinery using customer-supplied performance data linked to a logical diagnostic process.

The ICAS workstation is used for data acquisition, conditioning, performance analysis, trend and logsheet capture, and expert evaluation. Several types of data acquisition devices that process sensor output signals augment it. The ICAS workstation is also responsible for providing all user interface functions and long-term data storage. Within this environment, the Prognostic Enhancements to Diagnostics Systems (PEDS) program is focused on demonstrating prognostic enhancements using demand data interface protocols and displaying using pseudo sensor inputs or simple web-based interfaces.

3. US NAVY GAS TURBINE CBM INITIATIVE

The Navy has formed an open forum working group teamed to establish Gas Turbine CBM, with the goal to plan and execute integration of CBM technologies into gas turbines on all CG & DDG class ships. Installation of FADC (Full Authority Digital engine Controller) controllers on all gas turbines in the CG & DDG classes by the Life Cycle Managers over the next 8 years will provide the hardware and computing power required for equipment health assessment and monitoring. ICAS will provide the necessary connection allowing gas turbine health monitoring systems to provide assessments and recommendations to ships crew. New algorithms developed by the Navy, industry or the other programs will be incorporated as part of the FADC.

The planning phase was necessary to establish a plan, organize a working group, establish funding requirements for the life of the program with OPNAV sponsors, and develop the complete transition plan. Basic CBM development phase is designed to use the output of currently installed sensors to change some time-directed maintenance items to condition-directed items. In the advanced phase, a limited number of new sensors will be used to develop more condition directed tasks and start turning some corrective maintenance items into condition directed tasks before the effected components fail. The last phase, system-wide development will incorporate on-going and new R&D efforts into the development plan and complete system integration with ICAS. Most of the phases run concurrently and have parallel timelines.

4. INCORPORATING PROGNOSTICS

The approach for the PEDS program is to develop prognostic software that is modular and possess the capability for multiple transition opportunities. The role of a PEDS module in an existing system is depicted using the diagram in Figure 2. The figure illustrates the connections and communications between existing elements and the system enhancements. In the figure, proprietary interfaces or OSA-CBM middleware are used to "glue and hook" modules together. The figure shows the PEDS module's ability to interface directly with the existing system, it's HSI, and the decision support and logistics system using the proprietary interfaces defined by the existing system. This is accomplished using system specifications, such as a Demand Data Interface (DDI) as in the case of ICAS. In addition, the PEDS module has the ability to interface directly with any system

that uses OSA-CBM specifications (i.e. OSA-CBM Compliant Sensors and Processors, PEDS HSI) or systems that are enhanced to include the OSA-CBM specifications, which are represented by the dashed lines.

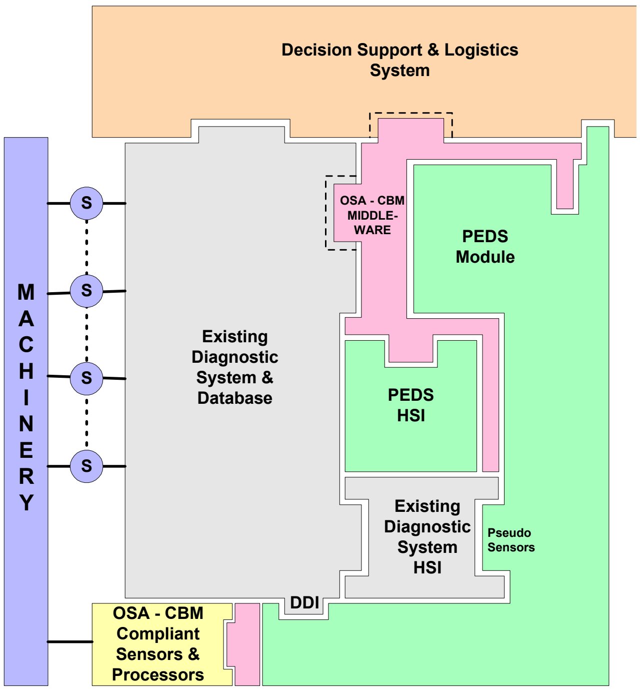

Figure 2 - PEDS and the Existing Diagnostic System

Evolving Open Systems Standards

Openness and open systems architecture is not a new concept in most parts of the engineering world. Being able to swap out a gear, bearing, shaft, chain, or even an engine is made possible through past efforts to standardize sizes and performance specifications. Equivalency is reduced to meeting performance (strength reliability, etc.) and known functional interfaces (physical, electrical, etc.). We tend to take this openness as a given, with little thought that it is usually the case for many situations. Electrical components (breakers, wire gauge, outlets, switches) followed a similar path and ultimately so is the electronics industry. While it is probably the case that these industries may have been slow to adopt these standards, at least with respect to today's Moore's Law expected timescales, in many ways it may be an engineering fait accompli. As the technology matures, there is a desire to box its function, quantitize its form factor, and structure its interaction with other system components. Philosophically, it could be argued that developing open standards minimizes the entropy gain in the engineering process.

This may be the case in the matured situation, but for the developing open system structure, the implementations are usually more time-consuming and certainly not the path of least resistance. It means learning new techniques, structuring in different ways, and in many cases carrying additional baggage. It is initially a disruptive process. Consider a turn of the century bearing manufacturer having to buy new materials, retool his machines, and change his finishing process. Also consider the market for the bearing manufacturer who didn't adapt to the engineering pressure to standardize. In addition, specifying performance is necessarily just as important as meeting a standard interface to accomplish true openness, modularity, and interchangeability.

The adaptation for software and information systems may be an even more challenging engineering endeavor given the nature of the differences between bits and atoms: what we can feel and see versus what we cannot see and must interpret through use cases and extrapolation. For a particular system integration task, an open systems approach requires a set of public component interface standards and may also require a separate set of public specifications for the functional behavior of the components. The development of the open-systems standards relevant to Condition-based Maintenance (CBM) and Prognostics and Health Management (PHM) development has been pursued by an International Standards Organization (ISO/TC 108/SC 5) committee, a consortium of condition monitoring companies (MIMOSA), and a DoD Dual-Use Science and Technology program (OSA-CBM) lead by Boeing. These projects were a start down the disruptive path of openness for health management systems.

Because the specification deals with the I/O only, the actual layers or "modules" can be coded in a manner as to allow for proprietary approaches, thus protecting the intellectual property of the developer. By applying the OSA-CBM specification, one can effectively communicate with a module being constructed by another developer without every knowing how the other module operates. Additional information about OSA-CBM can be found at http://www.osacbm.org and an OSA-CBM training manual can be found at http://www.osacbm.org/Documents/Training/TrainingMaterial/TrainingWebsite/index.html.

corrector schemes.

5. **Model-Based or Physics of Failure Based Prognostics**: Fully developed functional and physics-of-failure models to predict degradation rates given loads and conditions.

5. Prognostics Considerations

For a health management or CBM system to possess prognostics implies the ability to predict a future condition. Inherently probabilistic or uncertain in nature, prognostics can be applied to system/ component failure modes governed by material condition or by functional loss. Similar to diagnostic algorithms, prognostic algorithms can be generic in design but specific in terms of application. A prognostic model must have ability to predict or forecast the future condition of a component and/or system of components given the past and current information. Within the health management system architecture, the Prognostic Module function is to intelligently utilize diagnostic results, experienced-based information and statistically estimated future conditions to determine the remaining useful life or failure probability of a component or subsystem. Prognostic reasoners can range from reliability-based to empirical feature-based to completely model-based.

Some of the information that may be required depending on the type of prognostics approach used in the system include:

- Engineering Model and Data
- Failure History
- Past Operating Conditions
- Current Conditions
- Identified Fault Patterns
- Transitional Failure Trajectories
- Maintenance History
- System Degradation Modes
- Mechanical Failure Modes

Examples of prognostics approaches that have been successfully applied for different types of problems include:

1. **Experience-Based Prognostics:** Use statistical reliability to predict probability of failure at any point in time. May be augmented by operational usage information.
2. **Evolutionary/Statistical Trending Prognostics:** Multi-variable analysis of system response and error patterns compared to known fault patterns.
3. **Artificial Intelligence Based Prognostics:** Mechanical failure prediction using reasoners trained with failure data.
4. **State Estimator Prognostics:** System degradation or diagnostic feature tracking using Kalman filters and other predictor-corrector schemes.
5. **Model-Based or Physics of Failure Based Prognostics**: Fully developed functional and physics-of-failure models to predict degradation rates given loads and conditions.

6. Gas Turbine Performance Prognostics

Benefit of Technology

Fouling degradation of gas turbine engine compressors causes significant efficiency loss, which incurs operational costs through increased fuel usage or reduced power output. Scheduling maintenance actions based upon predicted condition minimizes unnecessary washes and saves maintenance dollars. The effect of the various maintenance tasks (washing and overhaul) on gas turbine engine efficiency is shown in the figure below.

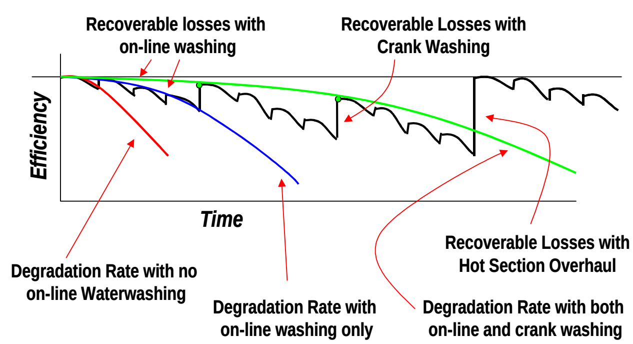

Figure 3. Effects of Washing on Efficiency and Overhaul

Currently, washes are performed on a preventative schedule of 50 hours for on-line washes and 500 hours for crank washes. This maintenance task is performed with no engineering assessment of conditional need or optimal time to perform. In addition to the loss of availability and maintenance time incurred, unnecessary washes generate an environmental impact with the used detergent. Clearly operating with a module that assesses condition and predicts the time to wash more appropriately would benefit the Navy.

Data and Symptoms for Development

The compressor wash prognostic model was developed using data from fouling tests taken at NSWCC in Philadelphia, PA and is an example of evolutionary prognostics approach. It is based upon specific system features and a simple model for compressor efficiency. In order to simulate the amount of salt the typical Navy gas turbine is exposed to on a normal deployment, a 9% salt solution was injected into the engine intake. Over the course of the entire test (3

days) approximately 0.0057m^3 of salt was used to induce compressor degradation at four different load levels (1/3, 2/3, standard and full load levels or "bells"). This method of testing was performed on both Allison 501 and LM2500 Units. Figure 4 shows a borescope image of the salt deposits on the LM2500 1st stage blading.

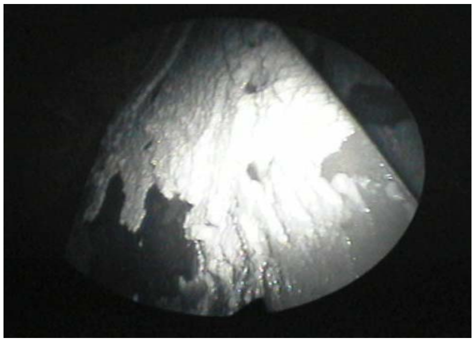

Figure 4 - Borescopic Image of Salt deposits: 1st stage

Compressor Performance Prognostics Module

The compressor performance prognostic module consists of data preprocessing and specific prognostic algorithms for assessing current and future compressor conditions. The data preprocessor algorithms examine the unit's operating data and automatically calculate key corrected performance parameters such as pressure ratios and efficiencies at specific load levels in the fashion already described. As fouling starts to occur in service, probabilistic classifiers match up corresponding parameter shifts to fouling severity levels attained from these tests with corresponding degrees of confidence. The techniques employed and processing in the module are shown in detail in Figure 5. As can readily be seen, the consideration of uncertainty is carried through the entire process to produce a confidence in the prediction.

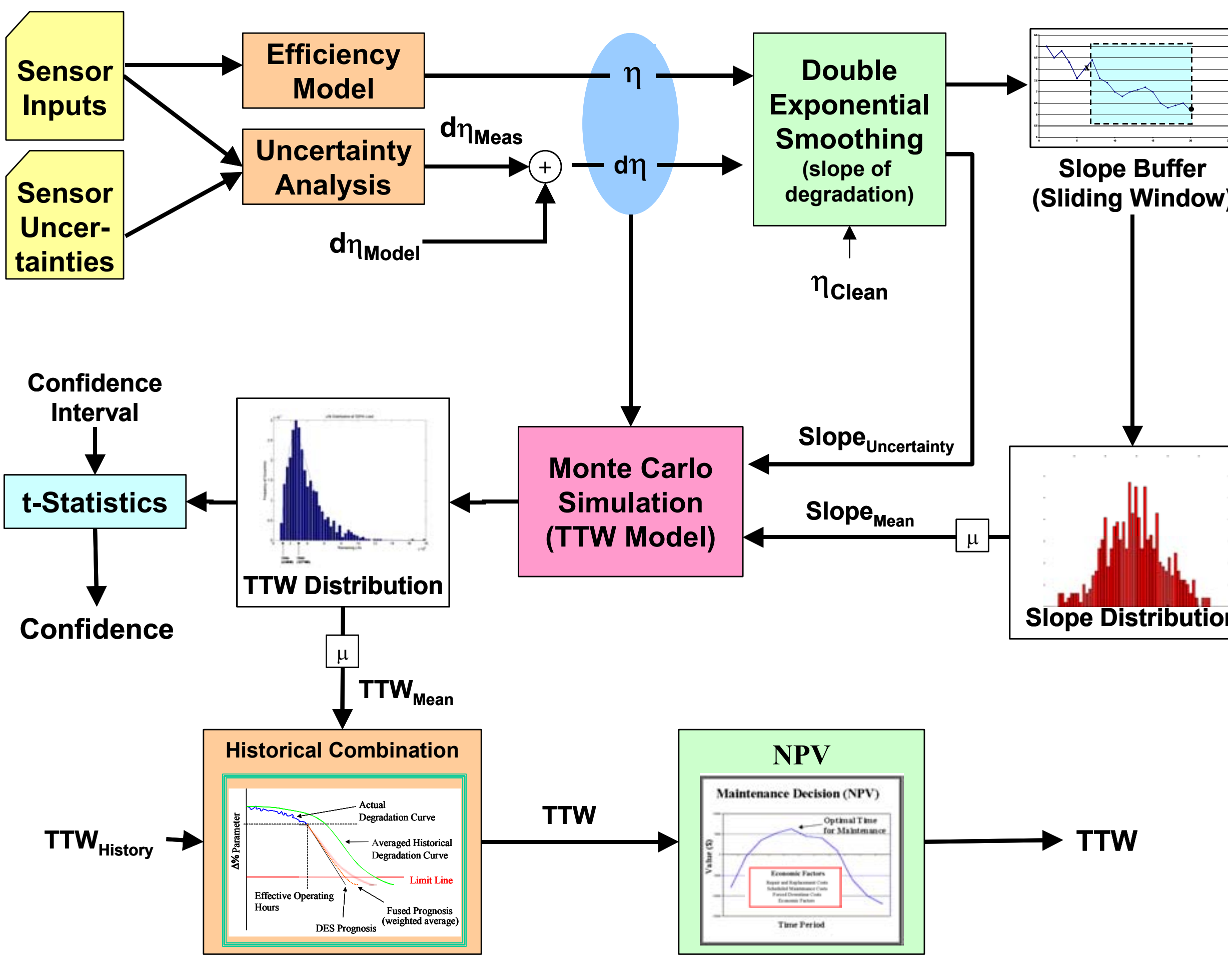

Figure 5 - Processing Flow for Compressor Performance Prognostics

A probabilistic-based technique was developed that utilizes the known information on how measured parameters degrade over time to assess the current severity of parameter distribution shifts and project their future state. The parameter space is populated by two main components. These are the current condition and the expected degradation path. Both are multi-variate Probability Density Function (PDFs) or 3-D statistical distributions. Figure 6 shows a top view of these distributions. The highest degree of overlap between the expected degradation path and the current condition is the best estimate of compressor fouling.

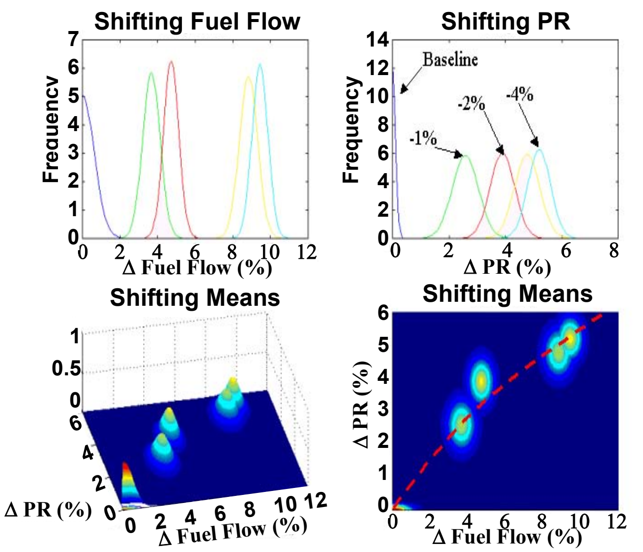

Figure 6 - Prognostic Model Visualization

To manipulate the data into the form of this model, the time dependency of the test results had to be removed because of the unrealistic fouling rates. The percent changes in static pressure ratio, fuel flow, and CDT were recast in terms of ¼ % pseudo-efficiency drops. This increment was chosen because it was the highest resolution that still permitted statistical analysis. With the assimilation of the data into these discrete bands, the statistical parameters (e.g., mean and standard deviation) can be ascertained for use in the prognostic model. Figure 6 shows the evolution of the compressor degradation for the LM-2500 test at 1% pseudo-efficiency drops (for visual clarity). The top two plots illustrate the distributions of pressure ratio and fuel flow respectively while the bottom two provides the joint probability distributions.

The compressor inlet temperature (CIT), outlet temperature (CDT), inlet total pressure (CIP_T) and discharge total pressure (CDP_T) can typically be used to find compressor efficiency. (Boyce 1995) However CDT, CDP_T are not standard sensors in most Naval platforms.

$$\eta_{adb} = \frac{\left[\left(\frac{CDP_T}{CIP_T}\right)^{\gamma-1/\gamma} - 1\right]}{\left[\left(\frac{CDT}{CIT}\right) - 1\right]} \tag{1}$$

In the event that total pressure measurements are not available, other methods can be used to approximate this efficiency calculation with other specific sets of sensors.

Once the statistical performance degradation path is realized along with the capability to assess current degradation severity, we needed to implement the predictive capability. The actual unit-specific fouling rate is combined with historical fouling rates with a double exponential smoothing method. This time series technique weights the two most recent data points over past observations. The following equations give the general formulation. (Bowerman, 1993).

$$S_T = \alpha y_T + (1-\alpha) S_{T-1} \tag{2}$$

$$S^{[2]}_T = \alpha S_T + (1-\alpha) S^{[2]}_{T-1} \tag{3}$$

$$\hat{y}_{T+\tau}(T) = \left(2 + \frac{\alpha\tau}{(1-\alpha)}\right) S_T - \left(1 + \frac{\alpha\tau}{1-\alpha}\right) S^{[2]}_T \tag{4}$$

Analysis of the degradation requires the simulation to predict the range of condition that might exist given the measurement and modeling uncertainties. This is accomplished using a Monte Carlo simulation with the mean and 2-sigma uncertainties. The resulting distribution is the range of Time-to-Wash predictions. Appropriate statistical confidence intervals can be applied to identify the mean predicted value. This estimate is updated with a weighted fusion from the predicted value and the historical degradation level derived from the fouling data. The results of this process are shown in Figure 7.

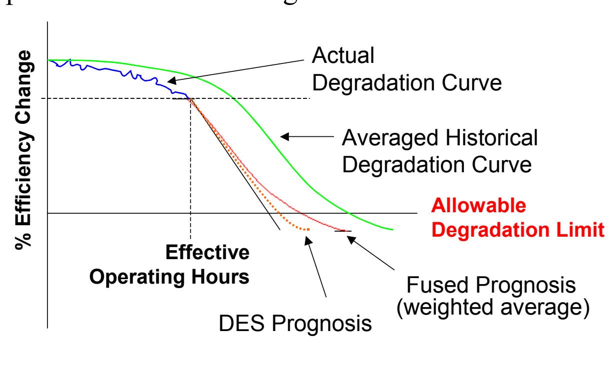

Figure 7 - Prediction of Degradation Rates

PEDS Implementation

The PEDS module implementation consists of translating the engineering code (in Matlab in this case) into an implemented “plug and play” module. The final compiling of the code is somewhat platform specific, but for Windows based applications the code can be written in C++ and compiled as a dll (dynamic linked library). The module currently supports OSA-CBM compliant XML (eXtensible Markup Language) and other documented data structures.

XML is an extension of Standard Generalized Markup Language (SGML) and has been a World Wide Web Consortium (W3C) recommendation since February 1998. XML is focused on describing information content and information relationships. XML is similar to HTML (commonly used in most web-based applications) except that, unlike HTML, XML does not have a predefined structure. The structure of the XML document is defined by a user-generated Document Type Definition (DTD) or schema. The display format of an XML document is also specified by the user/generator of the document using eXtensible Stylesheet Language (XSL). Therefore the same document can be displayed in multiple ways depending the consumer of the information. This separation of information content from its presentation is especially useful for user-centric interface designs.

A major advantage of the PEDS architecture is it’s modularity and code re-usability. The figure below shows the two possible deployment opportunities for the Compressor Wash prognostic algorithm, ICAS and Tiger™. As shown, the Initialization element is the only part of the code that is different between the two implementations. Therefore the other elements of the module are re-usable between the two approaches. This is possible because the code has been written to allow for a number of different input possibilities. Flags are set in the initialization element that indicates which inputs to expect for the current implementation. Therefore, this modularity of design allowed easy modification of the compressor water-wash module to interface with different existing monitoring systems, resulting in faster development time, and lower incurred costs.

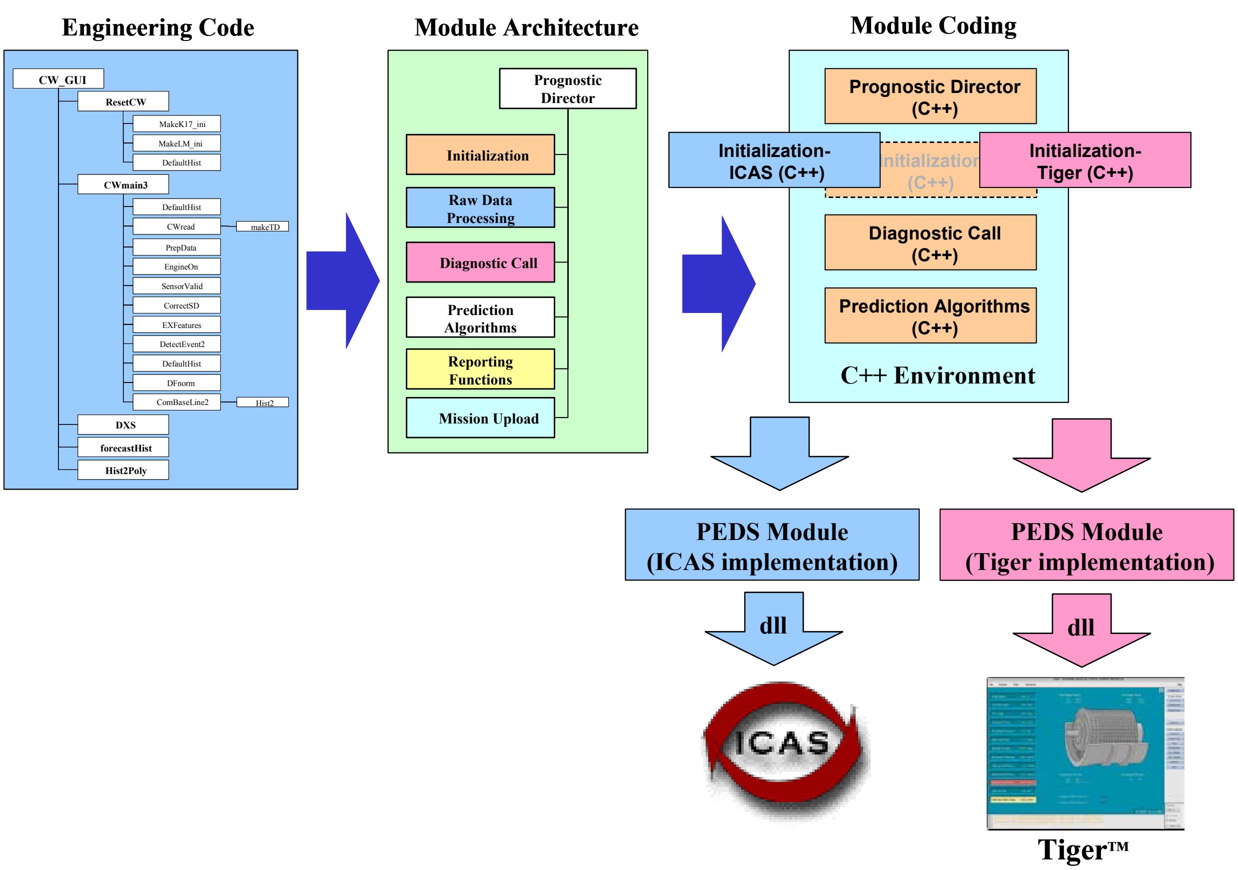

Figure 8. - Producing PEDS modules from Engineering Code

7. CONCLUSIONS

This paper discussed many concepts associated with prognostic module development under the PEDS (Prognostic Enhancements to Diagnostic Systems) program. A brief review of prognostic approaches, some implementation issues including current OSA developments, and an example of gas turbine performance prognostics was provided. Data availability, dominant failure or degradation mode of interest, modeling and system knowledge, accuracies required and criticality of the application are some of the variables that determines the choice of prognostic approach. The OSA implementations are being developed most readily in XML and the gas turbine module is being implemented in different Navy monitoring applications. Ultimately the ability to predict the time to conditional or mechanical failure (on a real-time basis) will be of enormous benefit and health management systems that can effectively implement the capabilities presented herein offer a great opportunity in terms of reducing the overall Life Cycle Costs (LCC) of operating systems as well as decreasing the operations/maintenance logistics footprint.

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